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A data-driven approach to manpower planning at U.S.–Canada border crossings

Mengqiao Yu [a], Yichuan Ding [b,*], Robin Lindsey [b], Cong Shi [c]

[a] Department of Civil and Environmental Engineering, The University of California-Berkeley, Berkeley, CA 94720, USA
[b] Sauder School of Business, University of British Columbia, Vancouver, V6T 1Z2 British Columbia, Canada
[c] Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI 48109, USA

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ABSTRACT

We investigate the staffing problem at Peace Arch, one of the major U.S.–Canada border crossings, with the goal of reducing time delay without compromising the effectiveness of security screening. Our data analytics show how the arrival rates of vehicles vary by time of day and day of week, and that the service rate per booth varies considerably by the time of day and the number of active booths. We propose a time-varying queueing model to capture these dynamics and use empirical data to estimate the model parameters using a multiple linear regression. We then formulate the staffing task as an integer programming problem and derive a near-optimal workforce schedule. Simulations reveal that our proposed workforce policy improves on the existing schedule by about 18% in terms of average delay without increasing the total work hours of the border staff.

1. Introduction

Peace Arch is the third busiest U.S.–Canada border crossing for passenger automobile traffic, connecting Surrey, British Columbia (Canada) and Blaine, Washington (U.S.). Trucks and commercial vehicles are not allowed to use this crossing, but it still operates 24 h a day. About 3500 light-duty vehicles (henceforth "vehicles") pass through it on a slow day, and as many as 4800 vehicles on a busy day. Waiting times to enter either the U.S. or Canada can reach four hours at certain times of the day. The monetary value of the time spent waiting in queues at U.S.–Canada border crossings is significant. In 2003, the U.S. Department of Transportation reported that the cost of delay while crossing the U.S.–Canada border exceeded $13.2 billion every year (Taylor et al., 2003). Nguyen and Wigle (2011) pointed out that, while staggering, this figure actually underestimates the cost since it excludes the costs firms incur in maintaining larger inventories as insurance against late shipments. This poses an important research question: is there an effective workforce policy at security checkpoints that can reduce waiting times without either increasing labor costs or compromising security or customs screening on either side of the border? The goal of this paper is to address this important question by studying traffic flows at Peace Arch: a heavily-used passenger-vehicle crossing. We use publicly available data on northbound traffic from Washington State to British Columbia.

Only recently has the border crossing problem become a topic of study in operations research. Attention has focused on so-called congestion-based workforce policies whereby the number of servers (i.e., the number of active inspection booths in

* Corresponding author.
E-mail addresses: mengqiao.yu@berkeley.edu (M. Yu), daniel.ding@sauder.ubc.ca (Y. Ding), robin.lindsey@sauder.ubc.ca (R. Lindsey), shicong@umich.edu (C. Shi).

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our context) is planned according to the scheduler's expectation of traffic rates, which can be based on historical data or experience. Major border crossing stations often include two stages of inspection. After vehicles complete the first stage, some are randomly selected for a second-stage inspection. Zhang (2009) studied the problem of minimizing delays in the first-stage inspection queue. Zhang et al. (2011) modeled a two-stage security checking system and determined the optimal fraction of passengers selected for second-stage inspection with the objective of balancing security and waiting times. Guo and Zhang (2013) further analyzed the equilibrium state under both no- and partial-information scenarios in a security-checking system equipped with a congestion-based workforce policy. Lin et al. (2014) developed multi-server queueing models to estimate border crossing delays and characterized the transient solutions to the queueing models. They also derived an optimal policy for opening and closing inspection booths over the course of a day, but unlike us they do not consider either workforce scheduling constraints or the potential dependence of service rates on time of day and workload (see below). Since we lack of data on the second-stage inspection, we follow Zhang (2009) in considering only a first-stage queue.

In terms of operations, toll collection on roads is similar in many aspects to border crossings, although delays at border crossings are usually much longer. Most research on toll roads has investigated either tolling for the purpose of pricing congestion or tolling for revenue maximization (see, e.g., Small and Verhoef (2007) and Nagae and Akamatsu (2006)). However, a few studies have examined manpower planning problems at toll collection plazas. Boronico and Siegel (1998) developed a capacity planning analysis for operations at toll collection plazas, and derived the optimal workforce policy. Kim (2009) built a nonlinear integer programming model to study the toll plaza optimization problem, where the cost of waiting times was determined from the steady-state solution of the queueing model. Other studies have discussed the impact of technology on toll plazas. For example, Al-Deek et al. (1997), in a case study, evaluated the benefit of implementing an electronic system (called E-Pass) for toll collection services. Our paper was inspired by Boronico and Siegel (1998), but our workforce optimization model is significantly more sophisticated because we take into account workforce scheduling constraints and variability in service rate per booth. As demonstrated by our data, both factors are important and statistically significant in the border-crossing setting we study.

Most of the literature mentioned above uses queueing theory to model waiting lines at border crossing stations or toll collection plazas. There is also an extensive literature on how to set up a workforce standard in a heavy-traffic queuing system. Whitt (2007) provides a comprehensive survey of the field. In most of the models in the border-crossing literature, arrival and service rates are time-independent, so that the system can be analyzed at its stationary state. However, in practice, most systems feature significant variability in arrival rates by time of day as is the case at Peace Arch (see Fig. 1). Moreover, supply and demand are often not well matched. Fig. 1 plots arrival rates (demand) and manpower (supply) over the course of a typical day at Peace Arch. The graph reveals a mismatch between the scheduled workforce (supply) and the arrival rates (demand), which suggests room for improvement. Such a mismatch leads to prolonged waiting times for travelers at peak demand times, and also a waste of staff time when booths are idled. This spurred us to design a new workforce policy that reallocates the number of booths in operation over the course of a day to better accommodate the variable demand while keeping total manpower fixed. We adopt a data-driven approach which forecasts the arrival rate in each hour of a day based on historical demand patterns, and then tries to better match the forecast demand with a feasible workforce schedule.

Our data-driven method also identifies predictors for service variability and uses these predictors in manpower planning. Conventional queueing models often assume that the service rate is either constant or depends only on queue length. However, our data reveals that queue length has little effect on service rate. The strongest predictors of service rate are

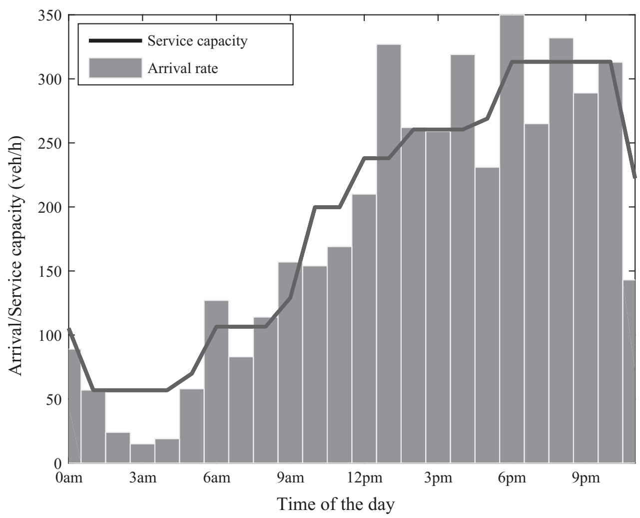

Fig. 1. Arrival rate and service capacity in each hour of a day.